

# What Makes A Good Story? Designing Composite Rewards FOR VISUAL STORYTELLING

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## The Visual Storytelling Task

 Given a photo stream, the machine is trained to generate a coherent story in natural language to describe the photos.



• Issue: previous methods focused on optimizing automatic metrics which are not especially designed for text quality

## ReCo-RL: Composite Rewards

- Our approach: design a reward function that correlates with story quality
- Specifically, use three different metrics:

#### Relevance

Extract important caption entities that appears in the image

#### Coherence

Estimate whether two sentences are coherent by a next sentence predictor

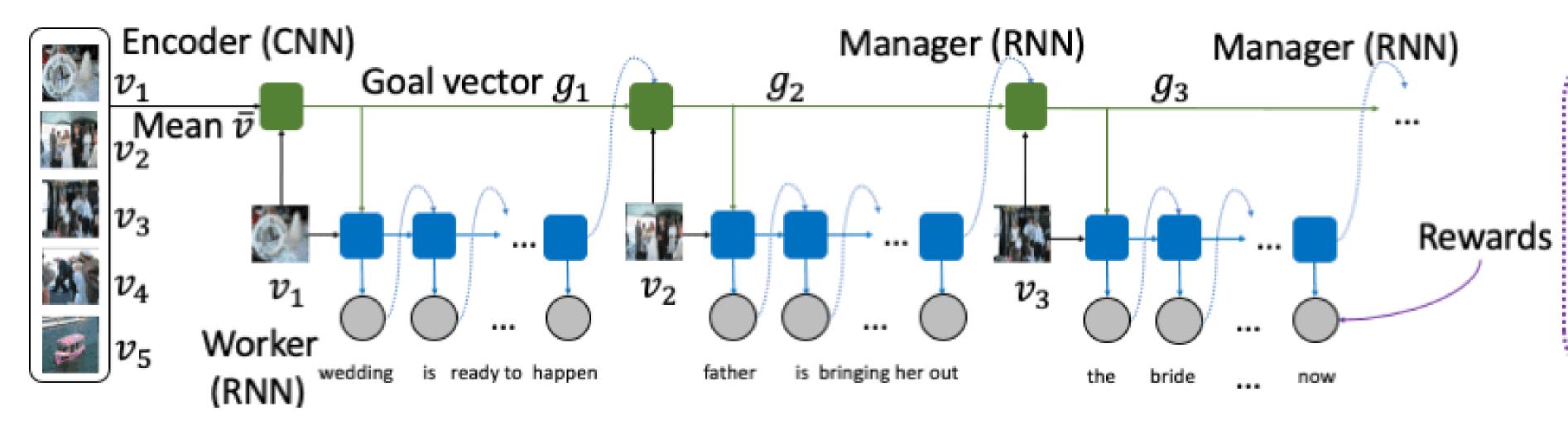
#### **Expressiveness**

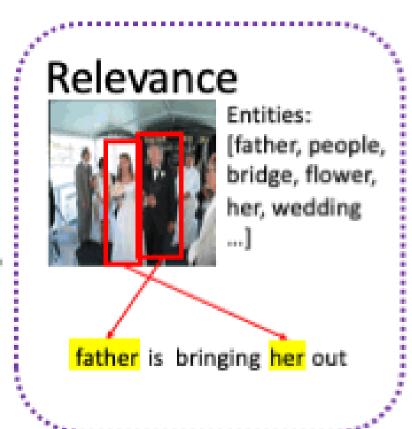
Penalize repeated patterns by comparing w/ previous sentences

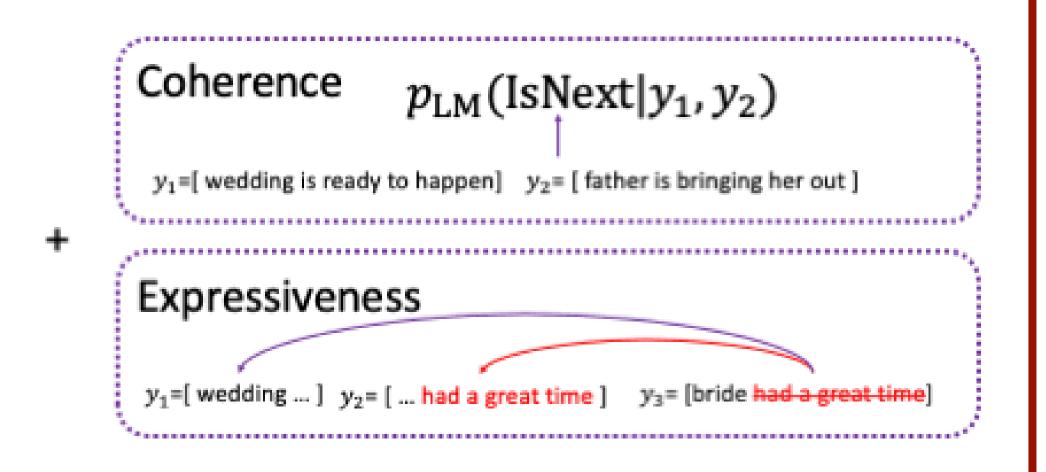
Train the model by REINFORCE and MLE

$$oldsymbol{ heta} \leftarrow oldsymbol{ heta} + \eta_1 rac{\partial J_{ ext{MLE}}(oldsymbol{ heta}, \mathcal{D}')}{\partial oldsymbol{ heta}} + \eta_2 rac{\partial J_{ ext{RL}}(oldsymbol{ heta}, \mathcal{D}')}{\partial oldsymbol{ heta}}$$

## Model Architecture: Manager-Worker w/ Three Rewards







## How to evaluate the text quality? Human Evaluation & Automatic Metrics

- Baselines: MLE; AREL; HSRL; ReCo-RL
- **Automatic Metric:** METEOR; BLEU; CIDEr; SPICE; ROUGH-L
- Our MLE/BLEU-RL/ReCo-RL are completive to SOTA
- Automatic metrics are not designed for visual storytelling
- Human evaluation: relevance, coherence, expressiveness in Table 2.
  - ReCo-RL outperforms other baselines
- Student's paired t-test with  $\rho$  < 0.05
- 862 turkers show substantial agreement
- ReCo-RL gets higher reward scores on test set in Table 3.
- BLEU-4 Method **METEOR ROUGE CIDEr SPICE** 35.2 29.3 13.6 **AREL HSRL** 34.8 **BLEU-RL** 35.2 14.4 30.1 8.3 33.9 ReCo-RL 29.9 8.6

Table 1: Comparison between different models on ME-TEOR, ROUGE-L, CIDEr, BLEU-4 and SPICE.

Method	Relevance	Coherence	Expressiveness				
HSRL	1.95	7.21	33.27				
<b>AREL</b>	3.27	9.90	34.98				
MLE	5.46	7.92	30.76				
<b>BLEU-RL</b>	2.17	12.40	30.41				
ReCo-RL	10.39	12.74	39.37				

Table 3: Comparison between different models on three rewards, i.e., Relevance, Coherence and Expressiveness.

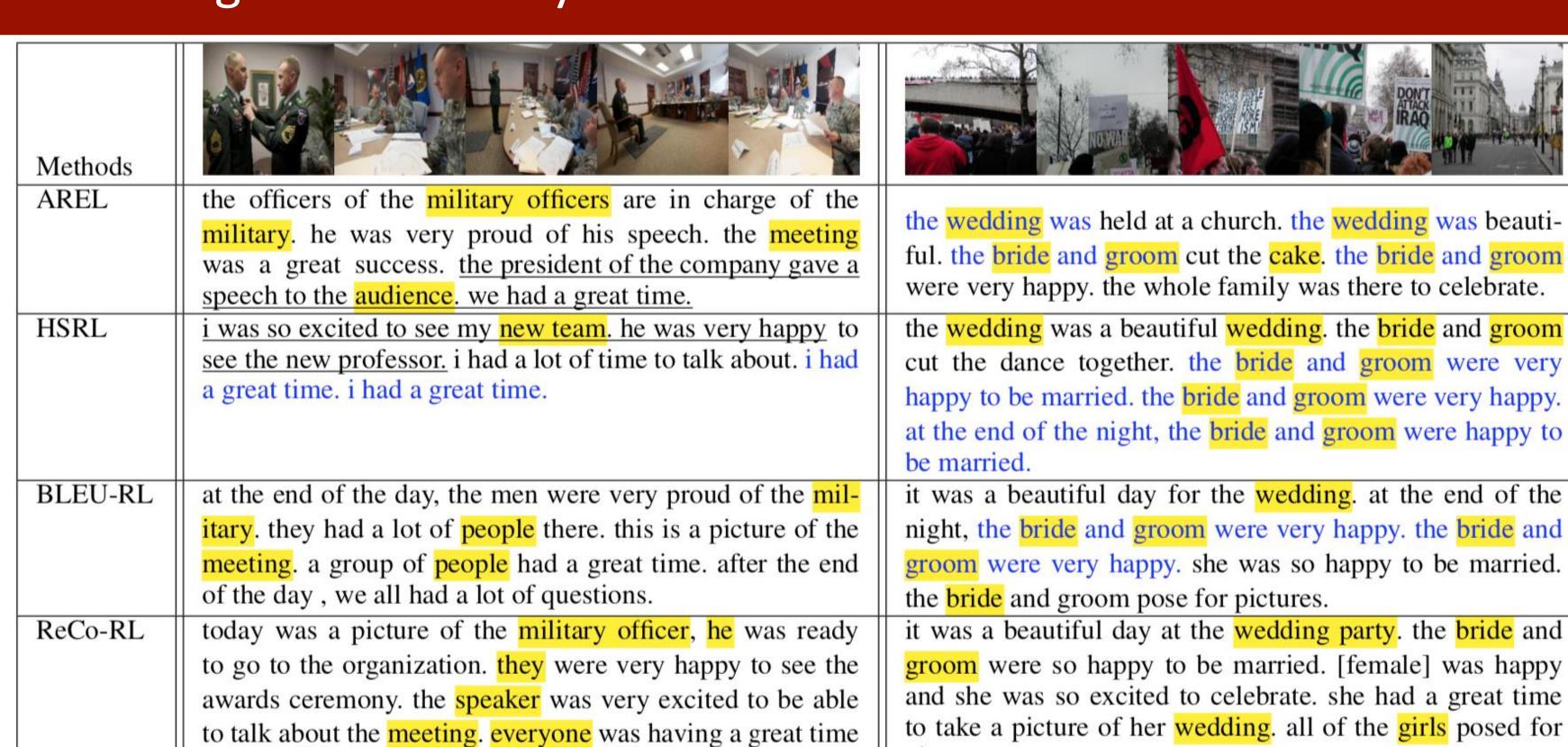
I	Aspects	AREL	ReCo-RI	. Tie	Agree	HSRL	ReCo-RL	Tie	Agree	MLE	ReCo-RI	L Tie	Agree	BLEU-RL	ReCo-RL	Tie	Agree
_	R	27.6%	62.2%	10.2%	0.72	36.1%	53.8%	10.1%	0.74	27.0%	64.1%	8.9%	0.49	17.6%	74.5%	7.9%	0.78
	C	31.3%	58.7%	10.0%	0.78	38.0%	51.9%	10.1%	0.80	34.3%	57.7%	8.0%	0.53	18.9%	72.3%	8.8%	0.71
	Е	32.4%	58.6%	9.0%	0.68	38.6%	53.3%	8.1%	0.72	30.5%	61.0%	8.5%	0.55	19.5%	71.5%	9.0%	0.62

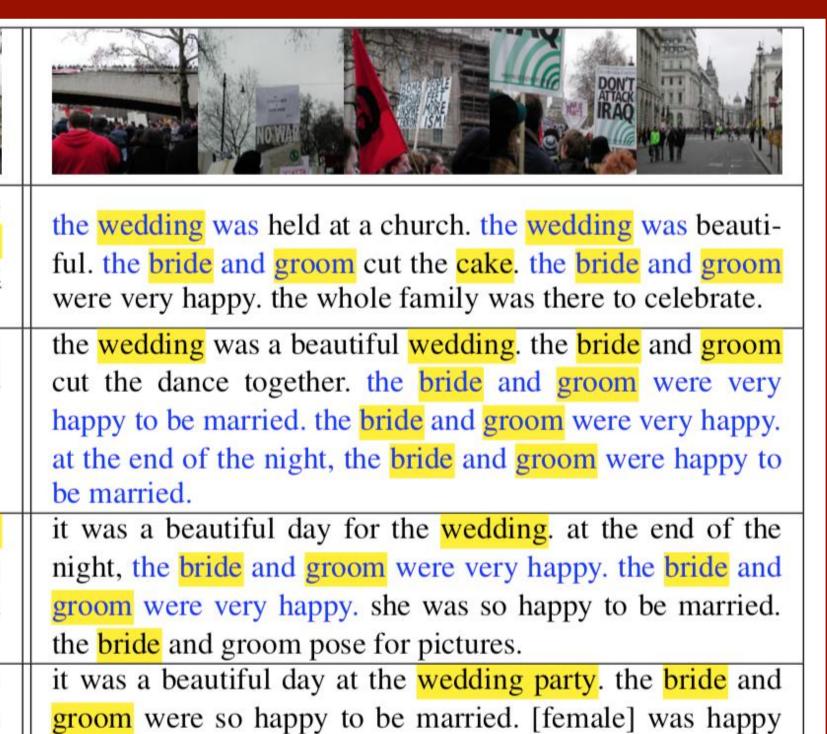
Table 2: Pairwise human comparison between ReCo-RL and three methods on Relevance, Coherence and Expressiveness.

## Qualitative Analysis: what does the generated story look like?

- BLEU-RL and HSRL generate uninformative segments.
- AREL generates topically uncoherent stories.
- ReCo-RL generates rare entites such as "sign" and "flags"
- Stories generated by ReCo-RL obtains higher reward scores.

Method		Quality Metrics				
Wiethod		R	C	Е	В	
BLEU-RL	a group of friends gathered together for dinner. the turkey was delicious. the guests were having a great time. at the end of the night, we had a great time. at the end of the night, we had a great time.	2.47	11.06	37.10	73.57	
ReCo-RL	a group of friends gathered together for a party. the turkey was delicious. it was a delicious meal. everyone was having a great time. after the party, we all sat down and talked about the night. my friend and [female] were very happy to drink.	3.32	16.99	41.71	78.51	





pictures.

a lot of people there.

to get together for the event after the ceremony. we all had